Cost-performance ratio for object detection

ST0256, Numerical Analysis - (2022-2)

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Medellín, September 20, 2022

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1 | Introduction

1.1 | Aim of the project

The idea is to find a cost-performance ratio comparing methods (and hopefully in hardware) like *YOLO*, *SSD*, *R-CNN* and *Fast R-CNN* for object detection, this focused mainly on autonomous driving, and thus find a way to implement autonomous driving at lower costs without losing much accuracy.

1.2 | Object Detection for Autonomous Driving

Is Autonomous driving only a *"Sci-fi dream"*? Or can we make it real?
Well, there have been a lot of projects and researchs to make this possible, and little by little we are getting cloese to it. But why bother to do autonomous driving? Is there any benefit? We have some benefits like **safety**, **mobility**, **environmental**, **efficiency**, even **economic** ones, a NHTSA (*National Highway Traffic Safety Administration*) study showed that motor vehicle crashes cost billions each year. Eliminating the majority of vehicle crashes through technology could reduce this cost [1].

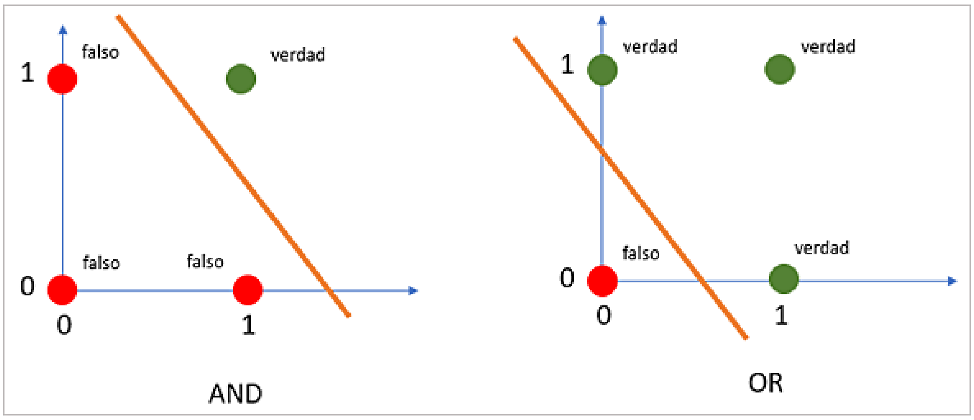
The future is a **Road to Full Automation**. Cars and trucks that drive us, instead of us driving them may offer transformative safety opportunities at their maturity. At this time, even the highest level of driving automation available to consumers requires the full engagement and undivided attention of drivers. There is considerable investment into safe testing, development and validation of automated driving systems. These automotive technology advancements also have the potential to improve equity, air pollution, accessibility and traffic congestion.

2 | Related work

2.1 | Multilayer perceptron

The multilayer perceptron is an artificial neural network (ANN) formed by multiple layers, in such a way that it has the capacity to solve problems that are not linearly separable, which is the main limitation of the perceptron (also called simple perceptron).

Linearly separable: Linearly separable data is data that can be separated by a line. To model this concept in a simple way, we are going to use the logical functions AND and OR (which are linearly separable) [2].



(a) *VANNIEUWENHUYZE, A. Artificial intelligence made easy: Machine Learning and Deep Learning at work. Recovered from: https://www.ediciones-eni.com/open/mediabook.aspx*

2.2 | Convolutional neural network

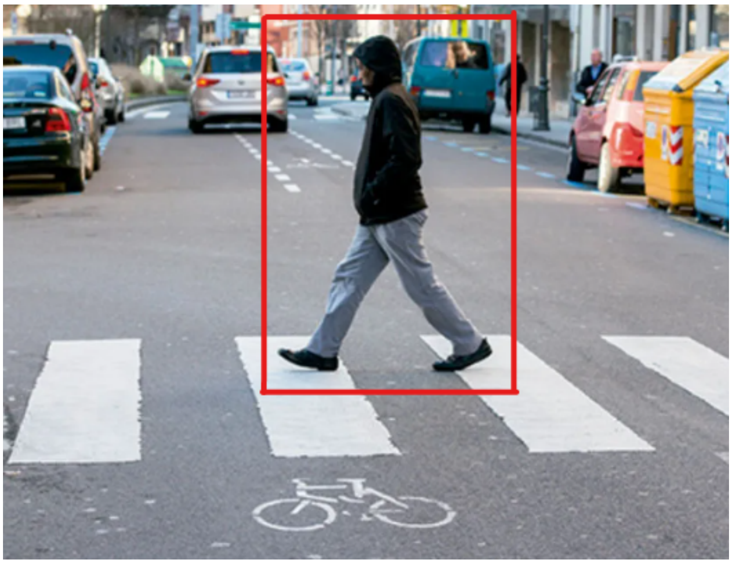
Convolutional Neural Networks are a type of artificial neural networks where "neurons" correspond to receptive fields in much the same way as neurons in the primary visual cortex (V1) of a biological brain. This type of network is a variation of a multilayer perceptron, however, because its application is carried out in two-dimensional arrays, they are very effective for artificial vision tasks, such as the classification and segmentation of images: which is effective in detecting of objects and automation of protocols allowing automatic driving in some models currently on the market.

Convolutional Neural Networks are a series of networks that were created thinking about how the brain works, capable of learning at different levels of abstraction: in the first layer, simple shapes, colors or edges are differentiated; in the next layer of the document, combinations of borders and colors can be distinguished; while the last layer looks at the shape in order to figure out what exactly it is [7]. This is the process that follows when classifying the images, but depending on the implementation there is a time when the neural network is trained so that it learns to distinguish objects by the properties in the image to be predicted. To do this, computers use filters or lenses to see the different features: one sees the diagonal edges, another the colors, etc. It works by passing filters over the entire image, scanning it, and then defining and classifying it.

2.3 | General process

Mainly it must be said that the detection of objects is not easy, generally the human eye is capable of detecting objects, regardless of the type of light, if it is blurred, the size of the object, the amount of the object it recognizes, etc. Such a task is not easy for a machine to perform, usually you have to turn a real world problem to a mathematical problem; Here convolutional networks come into action, whose simplest interpretation is to treat the problem in two-dimensional matrices and probabilistically. A convolutional network at the time of being trained begins to detect similarities between image information vectors through mathematical similarity techniques. The more iterations and opportunities to obtain information

from an image that describe the properties in a mathematical way, the better trained the network will be to predict objects in an image [5]. for instance:
For everything the process has to do with detecting a car or a pedestrian on the road, a vector would be used in this way, in the convolutional network to correctly decide whether or not what it is holding is what it already knows.



(a) *Person being detected*

$$\left\{\begin{array}{c} P_c \\ B_x \\ B_y \\ B_w \\ B_h \\ C_1 \\ C_2 \end{array}\right\} \left\{\begin{array}{l} 1 \\ 50 \\ 70 \\ 60 \\ 70 \\ 0 \\ 1 \end{array}\right\} \tag{2.1}$$

$P_c =$ If there is a car or a person.
$B_y =$ Center of object perimeter (y).
$B_x =$ Center of object perimeter (x).
$B_w =$ perimeter width.
$B_h =$ perimeter height.
$C_1 =$ If there is a car.
$C_2 =$ If there is a person.

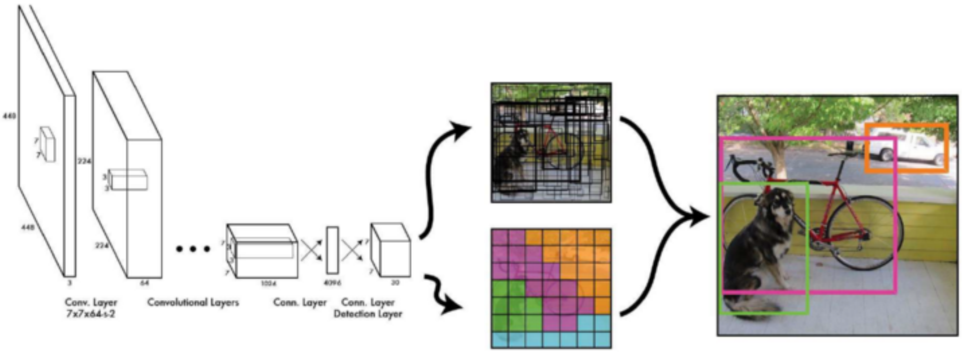
But this vector would only represent a correct detection vector of a person in an image with a region to predict. The previous problem is simplified because there is still the part in which the image is analyzed to detect the possible perimeters of objects to pass to the predictor and make its evaluation according to its training.
In the previous exercise, it gives us an idea of what happens internally, the convolutional network receives an image with vectors to be evaluated and gives a prediction based on the analysis and what has been learned. Also the values of the vectors are assigned according to the prediction and training of the convolutional network. These vectors have to be organized in a specific way, have a specific structure, and are analyzed differently depending on the technique or approach we use to approach this problem.
So far we have seen some parts of the prediction process in images with convolutional networks, recapitulating:

- **Training of the convolutional network:** moment in which our network is going to be trained to classify specific objects, where it is going to define the parameters to decide if an object is one thing or another.

- **Boundary box detection:** moment in which our program will discard and detect the best positioned boundary boxes, which we will predict according to the training of the convolutional network.
- **Prediction of elements in the boundary boxes:** the boundary boxes found are analyzed and evaluated to find similarity between the elements known by the network.

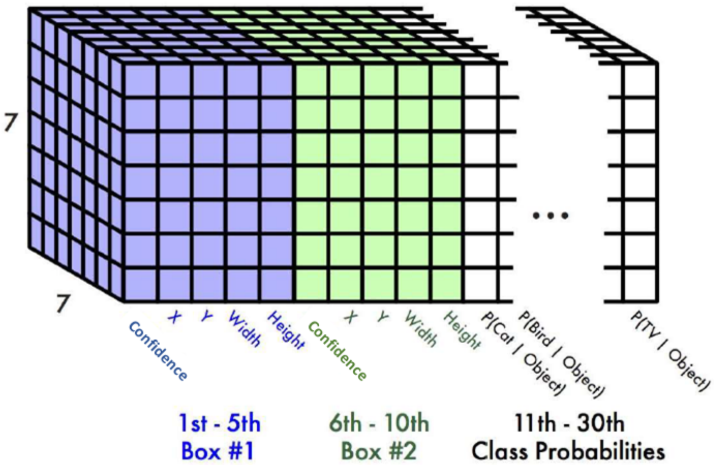
2.4 | YOLO (You Only Look Once)

You Only Look Once (YOLO) is a modern object detection algorithm developed and published in 2015 by Redmon et al. [4]. The name of the algorithm is motivated by the fact that the algorithm only looks once at the image and requires only one forward propagation pass through the neural network to make predictions unlike other state of the art object detection algorithms which work with region proposals and look at the image multiple times. YOLO uses a single end-to-end convolutional neural network which processes RGB images of size 448 x 448 and outputs the bounding box predictions for the given image:



(a) *Whole pipeline of YOLO's algorithm* [6]

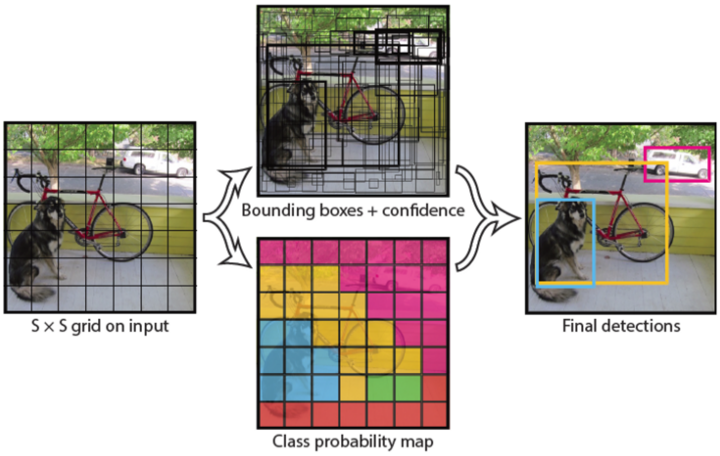
It basically reframes object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities [3]. The algorithm divides the input image into an SxS grid (in the paper $S = 7$). For each grid cell it predicts B bounding boxes (in the paper $B = 2$), where each bounding box consists of 4 coordinates and a confidence score for the prediction, and C class probabilities per grid cell taking the highest one as the final class. All of these predictions are encoded as an $SxSx(B * 5 + C)$ tensor which is being outputted by the neural network, as we can see in the following image.



(a) *The output tensor of YOLO* [6]

What the algorithm finally does, is identifying objects in the image and mapping them to the grid cell containing the center of the object. This grid cell will be responsible for predicting the final bounding box of the object and will have the highest confidence score. In the example of the previous image, each cell of the $7x7$ grid is represented by a vector of size 30 representing a particular area of the image. Each vector contains 2 bounding box predictions (5 values each) and 20 conditional class probabilities $P(class|object)$.

The first step upon extracting a valid prediction is to choose the bounding box with the higher confidence score and check if the confidence score is above a predefined threshold ($threshold = 0.25$ in the paper) to output it as a valid prediction. This confidence score represents the prior in the conditional probability for the class prediction stating the probability that the given grid cell is the center of an object with a correct bounding box. To extract the class prediction YOLO outputs the conditional probability with the highest score. YOLO spatially defines each bounding box by four coordinates $(X, Y, Width, Height)$, where (X, Y) represent the center of the bounding box relative to the cell, while $(Width, Height)$ represent the width and the height of the bounding box relative to the whole image. Because of this, a bounding box can be bigger than the cell where it was predicted. The cell is only used as the anchor point for the prediction. One disadvantage of this approach is the fact that every cell is able to predict only one object. If multiple objects are having their center points in the same cell, only one will be predicted.



(a) *SxS grid and final detections* [6]

2.5 | SSD (Single-Shot Detector)

2.6 | R-CNN (Region-Based Convolutional Networks)

2.7 | Fast R-CNN and Faster R-CNN

3 | References

[1] National Highway Traffic Safety Administration. Automated vehicles for safety, 2021.

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[3] Manish Chablani. Yolo - you only look once, real time object detection explained, 2017.

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[5] T. Roska T. Kozek and L. O. Chua. Genetic algorithm for cnn template learning," in ieee transactions on circuits and systems i: Fundamental theory and applications, vol. 40, no. 6, pp. 392-402, June, 1993.

[6] Sik-Ho Tsang. Review: Yolov1 — you only look once (object detection)., 2018.

[7] Wikipedia. Multilayer perceptron, 2022.